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PREDICTION OF GAS-OIL-RATIO BELOW THE BUBBLE POINT PRESSURE USING MACHINE LEARNING FOR NIGER DELTA REGION

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ABSTRACT

Determination of solution gas–oil ratio (GOR) is a very important requirement that helps in multiple production engineering and reservoir analysis issues. Gas-oil ratio is the ratio of the gas volume that comes from the produced oil at atmospheric pressure measured in standard cubic feet (SCF) to the volume of oil produced after the dissolved gas has evolved from it at the surface, measured in (STB). Before now, some empirical correlations existed that determines the solution gas–oil ratio however, they still prove unreliable due to the applied assumptions and their specification to operate only under a particular range of data. In this research, Machine learning models were trained to predict solution gas-oil ratio using Niger Delta reservoir fluid properties precisely for the pressure below bubble-point. The three-machine learning algorithm adopted are Deep neural network (DNN), Supper learner (SL) and Extreme Gradient Boost (XGBoost). A total number of 1083 of data set was obtained from PVT report from Niger-Delta and validated, out of which, 70% (758) were used to train the models, 15% (162) for testing and 15% (162) for validation. Quantitative and qualitative statistical analysis were carried out as to compare the performance and reliability of the new developed machining learning models with commonly used gas-oil ratio empirical correlations. The proposed Super Leaner algorithm model predicted better than the other selected machine learning models and GOR empirical correlations validated. The super leaner model gave the best result with the Rank of 0.144, followed by DNN and XGBoost having the Ranks of 0.419 and 0.503. GOR empirical models Glaso (1980), Standing (1947), Obomanu and Okpobiri (1987) having the Ranks of 0.41, 0.45 and 0.48 respectively. The findings from this research can be applied for estimation of the volumetric properties of hydrocarbon reservoir fluids without the need for conducting routine laboratory analyses.

Key Words: Correlation, Deep Neural Network, Machine Learning, Super Leaner Algorithm, Gas - Oil Ratio, Niger Delta

1 INTRODUCTION

The PVT (pressure-volume-temperature) fluid properties play a crucial role in the analysis and understanding of petroleum reservoirs. PVT correlations are commonly used to estimate fluid properties such as saturation pressure, solution gas-oil ratio, formation volume factors for oil, gas, and water, fluid viscosities, and fluid compressibility when laboratory measurements are unavailable [1]. The phase and volumetric behaviour of petroleum reservoir fluids is referred to as PVT, and it involves the analysis of gas, oil, and reservoir brine properties. Equations of state (EOS) and correlations are used to predict PVT properties in absence of experimental measurement. Equations of state methods are based on the fundamental principles of thermodynamics, while correlations are developed by fitting available regional data [2]. These properties can be obtained from a laboratory experiment using representative reservoir fluid samples. However, they are not always available because the cost of conducting PVT laboratory experiment repeatedly on an oil system is huge and the interpolation severity associated with reading tables and charts is unavoidable [3].

Among those PVT properties, Gas-oil-Ratio (GOR) is our primary interest in this study. The solution gas–oil ratio (GOR) is the quantity of gas dissolved at reservoir pressures in reservoir fluids [4]. It can also be described as the ratio of the gas volume that comes from the produced oil at atmospheric pressure measured in standard cubic feet (SCF) to the volume of oil produced after the dissolved gas has evolved from it at the surface, measured in STB. The gas-oil ratio (GOR) serves as a dynamic indicator, providing insights on the quantity of gas that is dissolved within the oil at varying depths and pressures. Solution gas-oil ratio is one of the most notable components of PVT correlations that has a very major impact on the oil viscosity, the compressibility of oil, oil formation volume factor and used also for calculating the in-situ total reservoir fluid rate.

The imprecise calculation of GOR will make several calculations and process evaluations challenging for petroleum and gas engineers. The most commonly calculations and process evaluations are inflow performance, material balance, initial- oil and gas-in-place prediction, reservoir simulations and economic analysis. Many researchers such as [5], [6], [7], [8], [9], [10], [11], [12], and [13] have developed empirical models for predicting Gas- Oil- Ratio. Majority of the empirical correlations were developed for pressure at the bubble point and the data set used are not from Niger- Delta except for [10] and [11].

The use of the machine learning approach in the petroleum industry has been increasing in the last two decades. [14] in 1994 is the first author that proposed the use of machine learning tool in forecasting the PVT properties using Artificial Neural Network (ANN) algorithm. Afterwards, researchers have trained Artificial neural network (ANN) models for estimating PVT properties. They reported from their findings a remarkable improvement over the commonly used empirical correlations with 45% to 25% reduction in the average error.

It can be seen from the body of literature, that Artificial Neural Network (ANN) model has gained popularity but recently, some authors have started investigating other machine learning algorithms as to address the limitations of ANN tool in forecasting reservoir fluid properties. ANN can learn complex non-linear relationships, even when the input information is noisy and less precise. However, the most important problem of ANN is the unexplained behavior of the network; when ANN produces a probing solution, it does not give a clue as to why and how which reduces the trust in the network

Some researchers like [15], [16], [17], [18], [19], [20], [21], [22] and [23] have investigated the use of new machine learning algorithms. Supper Learner, XG Boosts, Lightgbm, Neuro-Fuzzy Inference System (ANFIS), random Forest, and support vector machine are some of the new machine algorithm they have explored as to address some of the weakness of Artificial Neural Network. [15] used Neuro-Fuzzy Inference System algorithm to predict the solution oil-gas solution at the bubble point pressure (SCF/STB). They used 157 datasets from Iranian fields comprises of the bubble point pressure, gas gravity, API, and reservoir temperature. They concluded that their model outperformed some of the selected empirical correlations. [16] used adaptive neuro-fuzzy inference system (ANFIS) machine learning approach to develop a model that predicts gas-oil ratio below the bubble point. The authors used a total number of 376 data point from Sudanese oil fields. Mohammed and his team reported that their proposed ANFIS model performed better than other gas-oil ratio evaluated with an average absolute percent relative error of 10.60% and a correlation coefficient of 99.04. [17] adopted a support vector machine model to predict solution gas/oil ratio with an accuracy of 99%. In the study carried out by [19], they used a support vector machine model machine algorithm to predict solution gas-oil ratio with an accuracy of 98%.

[23] used a supervised deep neural network to estimate oil formation volume factor at bubble point pressure using 2994 Niger Delta region data. The author used a multi-layer neural network via the anaconda programming environment as a function of gas-oil ratio, gas gravity, specific oil gravity, and reservoir temperature. Two frameworks for modelling data using deep learning were employed which are TensorFlow and Keras. The result showed that DNN outperformed some of the existing correlations he evaluated with a mean average error of 0.05. [18] utilized three machines learning Artificial Neural Network (ANN) models, Functional Networks and Support Vector Machines to predict the solution oil–gas ratio for volatile oil and gas condensate reservoirs. The models were developed based on 17,941 data. The authors concluded that Support vector machine gave the best results with an average correlation coefficient of 99% and an average relative error of 0.12% as to compare with ANN and FNs. From the open literature, no much work has been done on solution gas- oil ratio using artificial intelligent tools for Niger – Data region particularly for two-phase reservoir. hence, the study focuses on developing a machine learning algorithm for predictingng gas-oil ratio for Niger Delta region.

1.1 Artificial Intelligence and Machine Learning

Artificial intelligence (AI), is an intelligence exhibited by machines, particularly computer systems. It is a field of research in computer science that develops and studies methods and software that enable machines to perceive their environment and use learning and intelligence to take actions that maximize their chances of achieving defined goals [24]. Recently, Artificial intelligence (AI), is the most important general-purpose technology that is rapidly entering industries, creating significant potential for innovations and growth. Machine learning is a subset of Artificial Intelligence (Fig. 2.2). In oil and gas industries, various types of data are collected from surface and subsurface to understand hydrocarbon and sensors are found to be the most prominent to collect these data in large numbers. AI are required to plot and analyze these data with technical analysis and intervention. The machine learning methods provides relationship between input variables and predicts the output. In machine learning, the physical behavior of the system is not interfered and the data associated with oil and gas industries are enormous and the process is very complicated for data correlations [14].

Classical Machine Learning (Fig. 1) and Deep Learning are dominant approaches used in Artificial Intelligence applications in the upstream sector and the whole oil and gas industry [25]. They are used to solve classification, clustering and regression types of problem. Artificial intelligence is bringing new approach is developing the oil and gas fields, one in which data is key. Petroleum engineers have shown a high degree of open-mindedness in utilizing new technology from different disciplines to solve oil and new petroleum engineering problems, as time changes and new technologies are developed, it is the job of petroleum engineers to utilize such innovations and improve them.

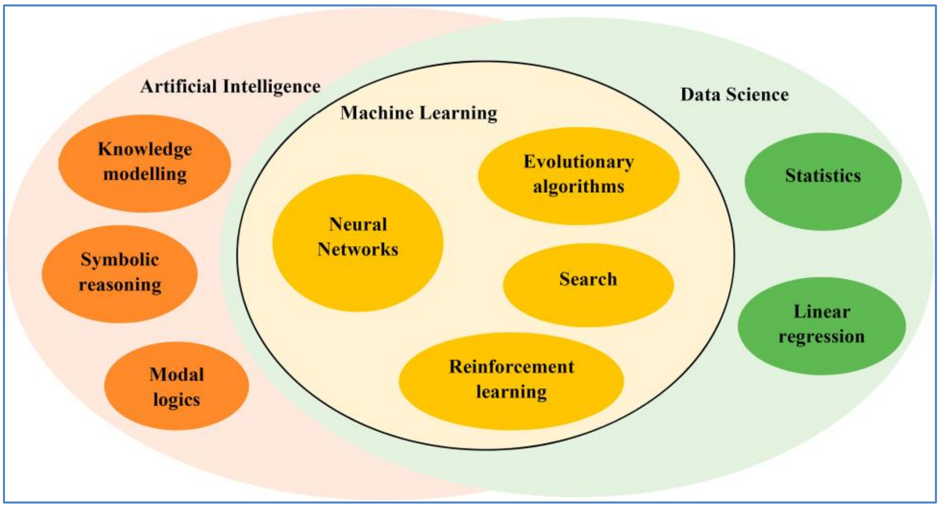

Figure 1: Venn Diagram Showing the Relationship Between Diversified Fields of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) [24].

1.2 Deep Neural Network

Deep learning, a subset of machine learning, is an artificial intelligence (AI) function that is used to learn from data without human supervision. It is useful in discovering patterns that lie within large datasets. It can also be considered as a set of data-analysis methods that includes classification, clustering, and regression. It uses multiple layers to progressively extract higher-level features from raw input and build efficient decision rules. Deep learning is a one-of-a-kind algorithm whose performance continues to improve because the more the data, the more the model is trained, resulting in outperformance of traditional models and algorithms.

In conventional machine learning techniques, important features need to be identified through a process called feature extraction in order for the learning algorithm to work. This reduces the complexity of the data and make patterns more apparent. Unfortunately, feature extraction is a separate and often a manual component in machine learning pipeline and it is time-consuming. The biggest advantage of deep learning algorithms is that they try to learn features from data in an incremental manner. The model first learns the basic constituents/low-level features before moving on to the high-level ones, thus eliminating the need of domain expertise and hardcore feature extraction.

There are three main types of deep learning algorithms: Multilevel perceptron, Convolutional Neural Network and Recurrent Neural Network. A multilevel perceptron is the component of a computing system designed in such a way that the human brain analyses and makes a decision. It is the building block of deep learning and solves the problem that seems impossible or very difficult by humans. CNN is a supervised type of Deep learning, most preferable used in image recognition and computer vision. CNN has multiple layers that process and extract important features from the image. RNN is a type of supervised deep learning where the output from the previous step is fed as input to the current step. RNN deep learning algorithm is best suited for sequential data Deep learning is used to create deep neural networks which are parallel-distributed information processing models that can recognize highly complex patterns within available data. In recent years, neural networks have gained popularity in petroleum engineering applications with many researchers recognizing that neural networks can serve in the petroleum industry to create more accurate PVT models.

1.2.1 Extreme Gradient Boost (XG Boost)

Machine learning is a core sub-area of Artificial Intelligence (AI) that gives it ability to learn. The learning process is achieved by using algorithms to discover patterns and generate insights from the original or measured data they are exposed . The machine learning algorithm adopted in this study is Extreme Gradient Boosting also known as XG Boot. It is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning library that helps to understand data and make better decisions. It provides parallel tree boosting and is the leading machine learning library for regression, classification, and ranking problems. The XG Boost algorithms builds on supervised machine learning, decision trees, ensemble learning, and gradient boosting. [26] gives more explanation to XG boost.

1.3 Super Leaner Model

The Super Learner Model (or Super Learner) is a powerful ensemble machine learning algorithm that aims to provide an optimal combination of predictive models for a given dataset. Developed originally by Mark van der Laan and colleagues, the Super Learner uses a theoretical framework that combines predictions from multiple algorithms to improve overall predictive performance. This approach is rooted in stacking and meta-learning, where multiple "base" models contribute to a final model that leverages the strengths of each. For more insight into Super Leaner see [27]. Fig. 2 shows the Schematic diagram of Super Leaner Model adopted in this Study for Soluble GOR BBP Prediction.

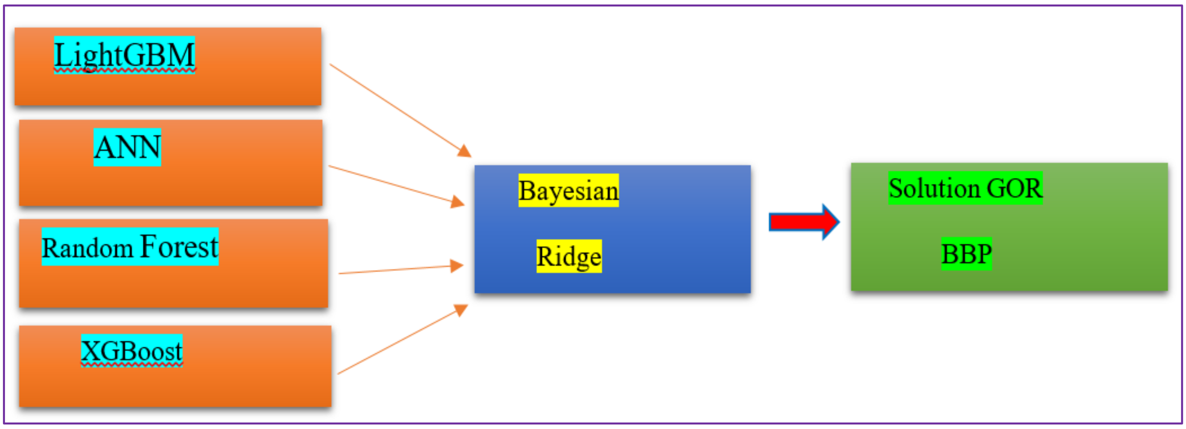

Figure 2: Schematic of Super Leaner Model Adopted in this Study for Soluble GOR BBP Prediction

2 METHODOLOGY

2.1 Data Collection

The data used were obtained from conventional PVT reports that derive the various fluid properties through liberation process from the Niger- Delta Region of Nigeria. 1383 data set which consist of the following fluid properties natural gas gravity of the gas phase, API gravity of the crude oil, temperature of the reservoir, pressure of the reservoir and soluble gas-oil ratio below bubble point pressure.

2.2 Data Validation

Before any experimental PVT data are used for design or study purposes, it is necessary to ensure that there are no errors or major inconsistencies that would render any subsequent work useless. Two such means of data validation are the Campbell diagram (Buckley plot) and the Mass Balance Diagram. These techniques were used to validate 1383 Niger- Delta data set and 1083 data set were found to be valid and were applied in this study.

2.3 Data Description

The functionality of gas-oil ratio with other parameters were established as to ascertain the relationship of the GOR to the input parameters. Data point of 1083 was used. These data points include natural gas gravity of the gas phase, API gravity of the crude oil; temperature of the reservoir and pressure of the reservoir. These data points are gathered from wells around the Niger Delta region. Table 1 presents the minimum; maximum, standard deviation and mean values of the data employed.

Table 1: Range of Values for the Input Parameters

Variable	Mean	Standard Deviation	Minimum	Maximum
Pressure (psi)	1645.2	969.19	115	6015
Gas specific gravity	0.675	0.0898	0.531	1.475
API	59.756	16.123	23.994	106.72
Temperature (^oF)	177.53	28.129	122.3	264
Gas-Oil Ratio (R_s)	425.5	275.44	42.6	1792

2.4 Machine Learning Models and Soft Ware Used

Statistica made by StatSoft and Matlab are the two major software used in this study. The Statistica was used to analysis the data, remove outliers, normalization, established the functional relationship between variable and determine the type of distribution that fit each parameter. Matlab is a high-level language programming software and was adopted in this research work, for training the machine learning models. For all the three machine learning models developed, the data were divided into 70% for Training, 15% for Testing and 15% for validation. The machine learning adopted are Deep neural network (DNN), XGboost and Super Learner.

2.5 Correlation Comparison

To compare the performance and accuracy of the new model to other empirical correlations, two forms of analyses were performed which are quantitative and qualitative screening. For quantitative screening method, statistical error analysis was used. The statistical parameters used for the assessment were percent mean relative error (MRE), percent mean absolute error (MAE), percent standard deviation relative (SDR), percent standard deviation absolute (SDA) and correlation coefficient (R).

For correlation comparison, a new approach of combining all the statistical parameters mentioned above (MRE, MAE, SDR, SDA and R) into a single comparable parameter called Rank was used [28]. The use of multiple combinations of statistical parameters in selecting the best correlation can be modeled as a constraint optimization problem with the function formulated as;

$$Min\ Rank = \sum_{j=1}^{m} S_{i,j} q_{1,j} \qquad (1)$$

Subject to $$\sum_{i=1}^{n} S_{i,j} \qquad (2)$$ With

$$0 \le S_{ij} \le 1 \qquad (3)$$

Where $S_{i,j}$ is the strength of the statistical parameter j of correlation i and q_{ij}, the statistical parameter j corresponding to correlation i. j = MRE, MAE, …. R^1, where R^1 = (1-R) and Z_i is the rank, (or weight) of the desired correlation. The optimization model outlined in Equations 1 to 3 was adopted in a sensitivity analysis to obtain acceptable parameter strengths. The final acceptable parameter strengths so obtained for the quantitative screening are 0.4 for MAE, 0.2 for R, 0.15 for SDA, 0.15 for SDR, and 0.1 for MRE. Finally, Equation 3 was used for the ranking. The correlation with the lowest rank was selected as the best correlation for that fluid property. It is necessary to mention that minimum values were expected to be best for all other statistical parameters adopted in this study except R, where a maximum value of 1 was expected. Since the optimization model (equations 1 to 3) is of the minimizing sense a minimum value corresponding to R must be used. This minimum value was obtained in the form (1-R). This means the correlation that has the highest correlation coefficient (R) would have the minimum value in the form (1-R). In this form the parameter strength was also implemented to 1-R as a multiplier. Ranking of correlations was therefore made after the correlations had been evaluated against the available database.

For qualitative screening, performance plots were used. The performance plot is a graph of the predicted versus measured properties with a 45^o reference line to readily ascertain the correlation's fitness and accuracy. A perfect correlation would plot as a straight line with a slope of 45^o.

3 RESULTS AND DISCUSSION

After training the laboratory data using the three-machine learning of DNN, Super Leaner and XG Boosts algorithms, the trained models were tested with 167 (15%) data points that were not previously used during training and validation processes. These data points were randomly selected by the MATLAB tool to test the accuracy and stability of the new trained model. The predictions and performance of the new artificial intelligent tools were compared with data from the field and the estimations from other gas-oil ratio empirical correlations like, [7], [5] and [12]. These empirical correlations were carefully selected having reported by some researchers of their excellent performance in predicting gas-oil ratio [30] and [31]. [12] is gas-oil ratio correlation that is developed using Niger-Delta region data. Table 2 and Figure 4 show the statistical comparison of the three-machine learning algorithm developed in this study with Super Leaner having the best rank of 0.0599 followed by DNN and XGBoost which have rank of 0.0732 and 0.1422 respectively. Figure 3 shows the mean square error (MSE) analysis as to confirm more the authenticity of the models, the super leaner model also outperformed other DNN and XGBoost models with the MSE of 0.5083. The best performance of Super leaner is due Super Learner is superior compared to the base learner since systematic errors of base learners are found and delineated on the final prediction to make it applicable in a variant of fields [29].

Table 2: Statistical Comparison of Models Developed in this Study

Statistical Indices	DNN	Super Learner	XGBoost
MAE	0.0924	0.0913	0.0967
MRE	0.0192	0.0089	0.0561
SRE	0.0183	0.0182	0.2518
SAE	0.0931	0.0918	0.362
R^2	0.9824	0.994	0.91
Rank	0.0732	0.0599	0.1422

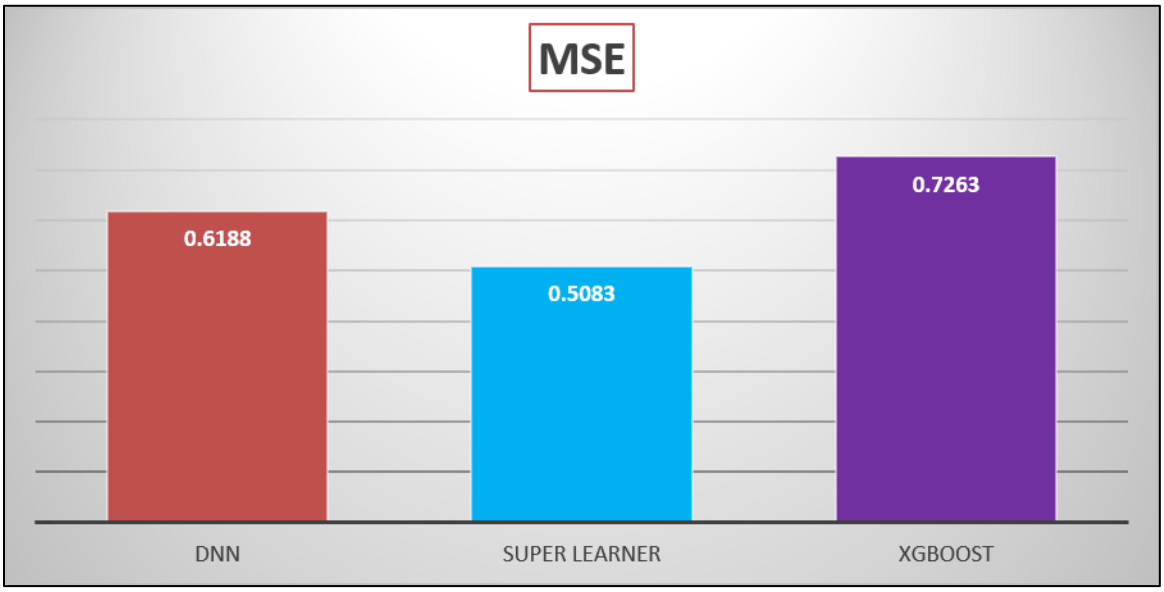

Figure 3: Mean Square Error of the Models

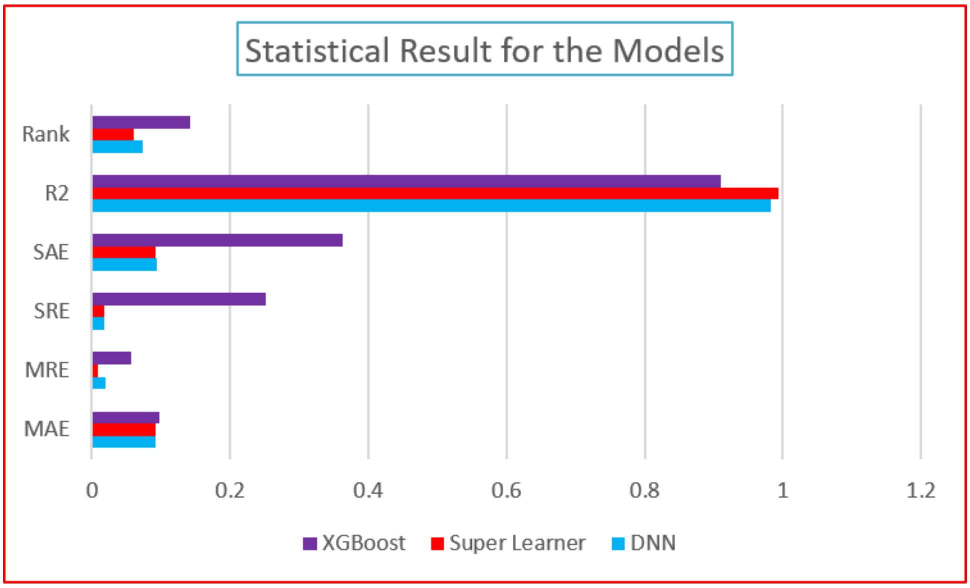

Figure 4: Statistical Comparison of All Three Models

3.1 Validation Results for Machine Learning and Empirical Models

For the validation and performance analysis, test data from XGBoost was generally used as to avoid biased result. The test data is 15% of the entire 1083 total data that was initially fed into the XGBoost machine but was not used during training and validation. These data were randomly selected by the XGBoost tool as to ascertain the accuracy and stability of the model. The same data points were used to estimate the prediction of gas-oil ratio from these correlations and their associated statistical indicators used for model performance. The performance of all the newly developed models were compared with the predictions from other specially selected empirical correlations such as [5], [7] and [12]. These predictive correlations were carefully selected, having some of the mathematical models been developed specifically for the prediction of GOR BBP in Niger-Delta regions and some authors has reported that [7] and [5] are the best correlation that can be used to predict GOR BBP for Niger Delta. Figure 4 showed that Super Leaner performed better than all the validated models with a Rank of 0.05611, MAE of 0.0913, MRE of 0.0189, SRE of 0.0918, SAE of 0.0918, and of 0.994. The research agreed with findings from [30] that Super Leaner is the best algorithm for predicting reservoir PVT properties. DNN came second with the rank of 0.05911 and R values of 0.9824, followed by empirical correlation developed in this study with a rank value of 0.0681 and R of 0.98. [7] performed better than all the empirical correlations evaluated with the rank of 0.1778 and R value of 0.981 and result agreed with the work done [30], [31].

Table 3: Statistical Comparison for validated Models

Models	MAE	MRE	SRE	SAE	R	Rank
Obomanu and Okpobiri (1987)	0.1591	0.0673	0.5024	0.6181	0.973	0.817
Standing (1947)	0.1427	0.1913	0.3575	0.5379	0.968	0.731
Glaso (1980)	0.1037	0.1544	0.2983	0.4958	0.981	0.553
XGBoost	0.0967	0.0561	0.2518	0.362	0.910	0.502
DNN	0.0924	0.0192	0.0383	0.1931	0.982	0.410
Super Leaner	0.0313	0.0119	0.0172	0.0918	0.994	0.144

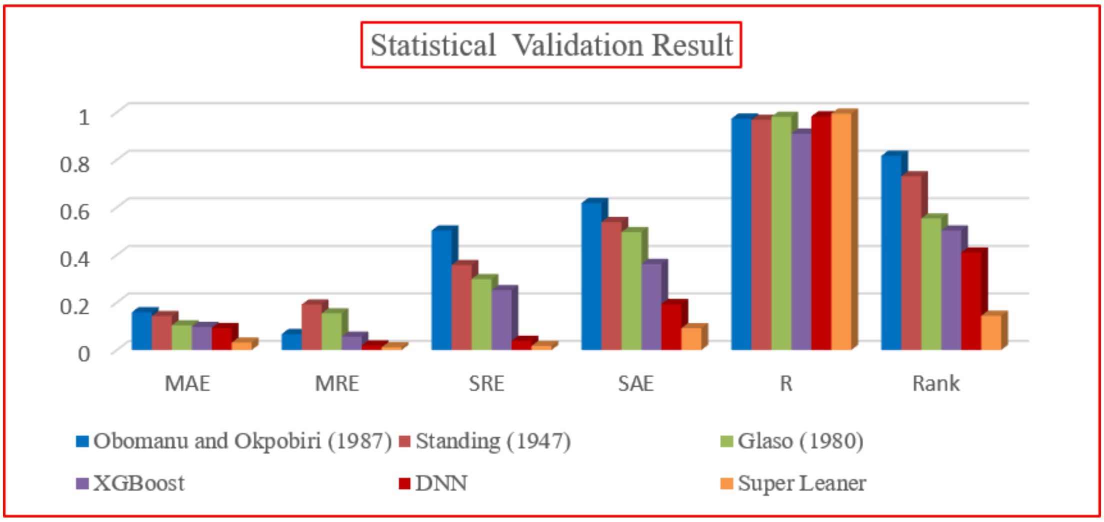

Figure 4: Statistical Comparison of all the validated Models

3.2 Performance Plot Results

Cross plots of the predicted versus experimental data for solution gas-oil are illustrated in Figures 5 to 7. It is a plot of predicted versus measured properties with a 45° reference line to readily ascertain the correlation's fitness and accuracy.

Figures 5 and 7 which are the Cross plots of Super Leaner Model and Deep Neural Network show the tightest cloud of points around the 45° line with very good clusters at low band, indicating the excellent agreement between the experimental and the predicted data values when compared to Figures 6 to 8. In addition, this indicates the superior performance of the machine learning model over empirical correlations evaluated. The accuracy of the models indicates that the Machine intelligent model (Super Leaner Model and Deep Neural Network) did not over fit the data, which implies that they were successfully trained.

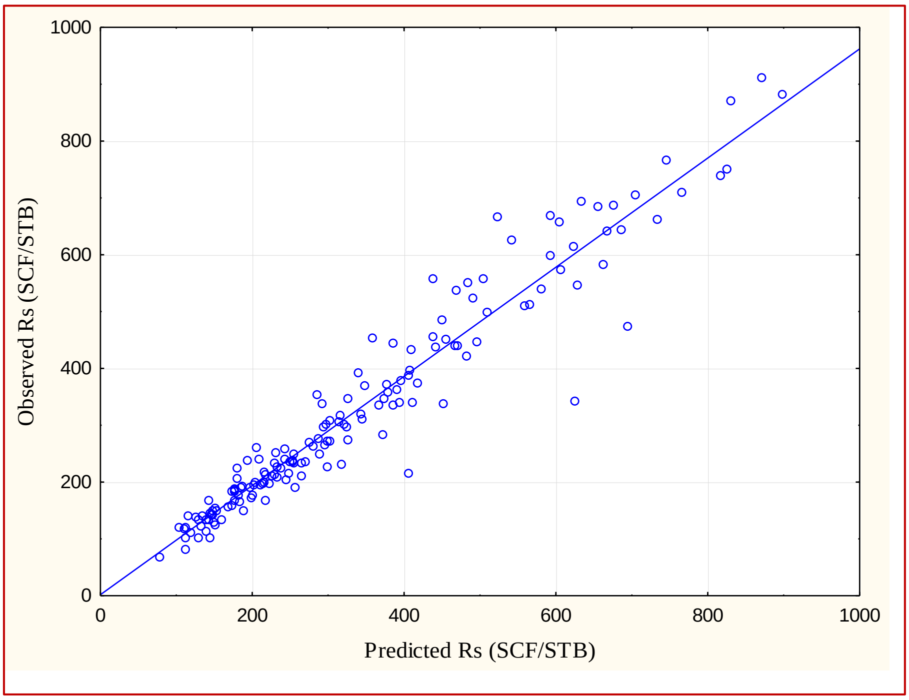

Figure 5: Cross Plot of Predicted and Observed GOR for the Test Data for Super Learner

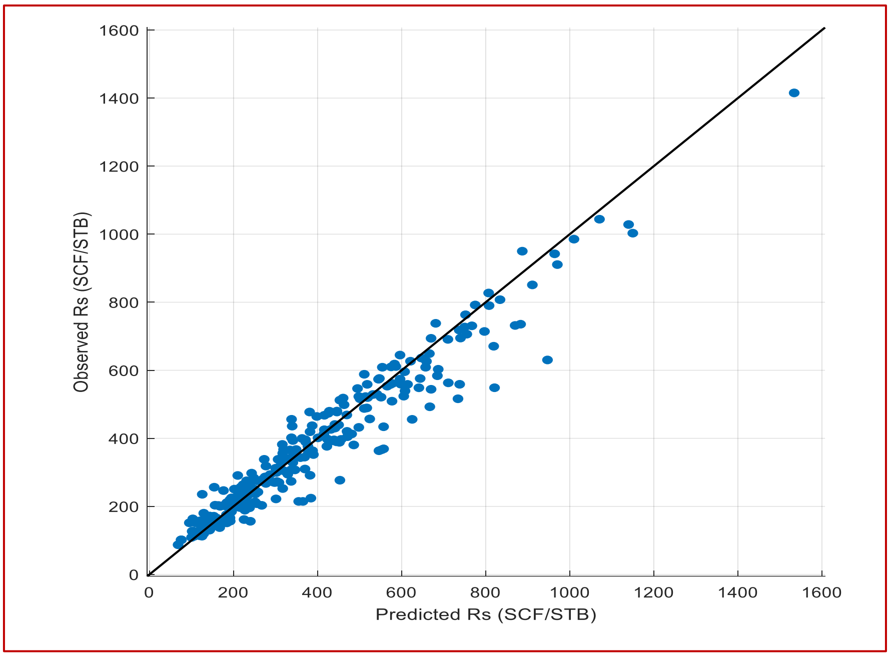

Figure 6: Cross Plot of Predicted and Observed GOR for XGBoost using the Test Data

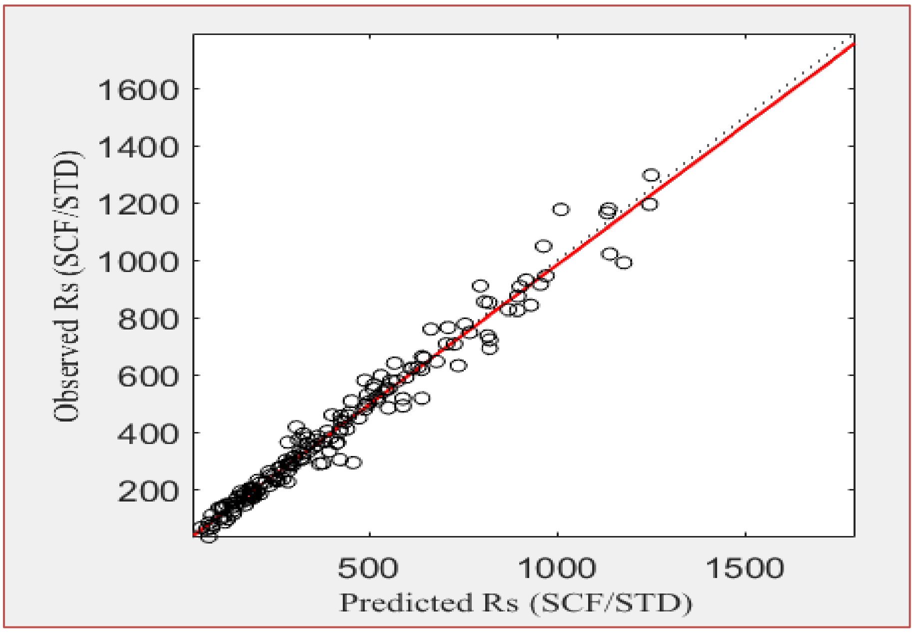

Figure 7: Cross Plot for the Test Data Using DNN

4 CONCLUSION

This article demonstrates the idea of application of machine learning algorithms, such as DNN, XGBoost and Super Learner to predict soluble gas-oil ratio for pressure below bubble point pressure based on laboratory measured data. The study showed that Super Learner might be promising tools for GOR prediction and can be applied to reduce the cost of laboratory measurements. It was found that Super Learner integrates the merits of base machine learning algorithms, its capability in forecasting a more accurate GOR is improved significantly. In addition, it has a potential to increase the accuracy of reservoir fluid properties modeling of crude oil where some data are not available. The main advantage of using machine learning and intelligence methods in the estimation of soluble gas-oil ratio below bubble point is that with knowing examples of previous patterns they can be easily trained and put to effective solving of unknown or untrained instances of the problem as was the case here. The results confirm the superior performance of the proposed Super Learner model in predicting GOR than DNN, XGBoost and other empirical correlations investigated with the rank numerical value of 0.144.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare no conflicts of interest regarding this manuscript".

REFERENCES

[1] Bahadori, A. Fluid Phase Behavior for Conventional and Unconventional Oil and Gas Reservoirs; Gulf Professional Publishing, 2016.

[2] Peng, D.Y., Robinson, D.B., 1976. A new two-constant equation of state. Ind. Eng. Chem. Fundam. 15, 59–64. https://doi.org/10.1021/i160057a011.

[3] Saleh, A.M., Mahgoub, I.S., Asaad, Y., 1987. Evaluation of Empirically Derived PVT Properties for Egyptians Oils. https://doi.org/10.2118/15721-ms.

[4] Ahmed,T.(2013). Equations of State and PVT Analysis; Elsevier.

[5] Standing M. B. (1947). "A Pressure-Volume-Temperature Correlation for Mixtures of California Oils and Gases," Drill & Prod. Pract., API (1947), pp 275-87.

[6] Vazquez, M., Beggs, H.D., 1977. Correlations for fluid physical property prediction. In: Proc. - SPE Annu. Tech. Conf. Exhib. 1977-Octob. https://doi.org/10.2118/6719- ms.

[7] Glaso, O., (1980). "Generalized pressure-volume-temperature correlations". J. Petrol. Technol. 32, 785–795. https://doi.org/10.2118/8016-pa

[8] Al-Marhoun, M. A. (1992). "New Correlation for formation Volume Factor of Oil and Gas Mixtures," JCPT, pp. 22

[9] Dokla, M.E., Osman, M.E., 1992. Correlation of PVT properties for UAE crudes. SPE Form. Evaluation 7, 41–46. https://doi.org/10.2118/20989-pa.

[10] Fattah, K.A., Lashin, A., 2018. Improved oil formation volume factor (Bo) correlation for volatile oil reservoirs: an integrated non-linear regression and genetic programming approach. J. King Saud Univ. - Eng. Sci. 30, 398–404. https://doi.org/10.1016/j. jksues.2016.05.002.

[11] Karimnezhad, M., Heidarian, M., Kamari, M., Jalalifar, H., 2014b. A new empirical correlation for estimating bubble point oil formation volume factor. J. Nat. Gas Sci. Eng. 18, 329–335. https://doi.org/10.1016/j.jngse.2014.03.010.

[12] Obomanu, D.A., Okpobiri, G.A., 1987. Correlating the pvt properties of nigerian crudes. J. Energy Resour. Technol. Trans. ASME 109, 214–217. https://doi.org/10.1115/ 1.3231349.

[13] Ikiensikimama, S.S., Ajienka, J.A., 2012. Impact of PVT correlations development on hydrocarbon accounting: the case of the Niger Delta. J. Petrol. Sci. Eng. 81, 80–85. https://doi.org/10.1016/j.petrol.2011.12.017.

[14] Ali, J.K., (1994). Neural Networks: "A New Tool for the Petroleum Industry? EPCC 1994. In: Society of Petroleum Engineers" - European Petroleum Computer Conference, pp. 233–242. https://doi.org/10.2523/27561-ms.

[15] Zamani, H. A.; Rafiee-Taghanaki, S.; Karimi, M.; Arabloo, M.; Dadashi, A. Implementing ANFIS for Prediction of Reservoir Oil Solution Gas-Oil Ratio. J. Nat. Gas Sci. Eng. 2015, 25, 325–334.

[16] Mohammed, M. A. A., Alakbari, F. S. Nathan, C. P and Mohyaldin, M. E. (2022) "Determination of the Gas−Oil Ratio below the Bubble Point Pressure Using the Adaptive Neuro-Fuzzy Inference System (ANFIS)" ACS Omega, 7, pp. 19735-19742.

[17] Adeyemi, A., and Owolabi, O. (2021). "Prediction of bubble point solution gas oil ratio using support vector machine". Journal of Petroleum Exploration and Production Technology, 11(6), 2597-2607.

[18] Zadeh, L. A. Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems: Selected Papers by Lotfi A Zadeh (Advances in Fuzzy Systems-Applications and Theory); World Scientific: 1996; pp 394–432.

[19] Ibe, C. C., and Akpan, O. E. (2023). "Prediction of bubble point solution gas oil ratio using artificial neural networks". Journal of Petroleum Science and Engineering, 212, 110494.

[20] Al-amoudi, L.A., Salem, B., Fahd, K., Patil, S. and Baarimah, S.O., (2019). "Development of Artificial Intelligence Models for Prediction of Crude Oil Viscosity

[21] Mbachu, I. I. and Peter, A. O. (2024). "Gas- Oil Ratio Prediction Using Machine Learning Procedures for Niger Delta Region", International Journal of Scientific Research and Engineering Development— Vol. 7, 743 -753

[22] Origbo, O. A. and Mbachu I. I. (2024). "Forecasting Dead Oil Viscosity Using Machine Learning Processes for Niger Delta Region", International Journal of Current Science Research and Review, Volume 7. p. 820-830

[23] Koffi, I. U. (2021). "A Deep Learning Approach for the Prediction of Oil Formation Volume Factor", SPE-208627-STU.

[24] Russell, S. J., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach (4th ed.).Pearson.https://www.amazon.com/Artificial-Intelligence-A-Modern-Approach/dp/0134610997

[25] Sircar, A., Yadav, K., Rayavarapu, K., Bist, N., and Oza, H. (2021). Application of machine learning and artificial intelligence in oil and Gas Industry, Petroleum Research

[26] Chen, T. Yang, H. Li, Q. and Yu, Y. (2013). "General functional matrix factorization using gradient boosting. In Proceeding of 30th International Conference on Machine Learning". (ICML'13), volume 1, pp. 436{444)

[27] Polley, E.C. and Van Der Laan, M.J. (2010). "Super Learner in Prediction"; U.C. Berkeley Division of Biostatistics: Berkeley, CA, USA, p. 266. 80

[28] Ikensikimama, S. S. (2009). "Reservoir Fluid Property Correlations" Advances in Petroleum Engineering, Chi Ikoku Petroleum Engineering Series, IPS Publications, Port Harcourt

[29] Hemmati-Sarapardeh A, Aminshahidy B, Pajouhandeh A et al (2016 A soft computing approach for the determination of crude oil viscosity: light and intermediate crude oil systems. J Taiwan Inst Chem Eng 59:1–10

[30] Sleiti, A. K., Wahib, A., Al-Ammari, W. Abdelrazeq, A M. El-Naas, M. Rahman, M. A., Barooah, A. Hasan, R. and Manikonda, K. (2021). "Comprehensive Assessment and Evaluation of Correlations for gas-oil Ratio, Oil Formation Volume Factor, Gas Viscosity, and Gas Density Utilized in Gas Kick Detection", Journal of Petroleum Science and Engineering 2021, https://doi.org/10.1016/j.petrol.2021.109135

[31] Owalobi, O. N. and Mbachu, I.I. (2024). Comprehensive Evaluation of Bubble-Point and Below Bubble Point Gas - Oil Ratio (Gor) Empirical Correlations for Niger Delta Region, Journal of Scientific and Engineering Research, 11(1):67-76